Optimization-based iterative learning control for robotic manipulators

Armin Steinhauser, Goele Pipeleers and Jan Swevers
Division PMA, Department of Mechanical Engineering
Katholieke Universiteit Leuven
Celestijnenlaan 300B, B-3001 Heverlee, Belgium
Email: armin.steinhauser@kuleuven.be

1 Introduction

Iterative learning control (ILC) has been intensely researched for over 30 years to improve the performance of repetitive processes [1]. Most ILC algorithms use a known, but potentially inaccurate model to compute the next iteration's control signal. The majority of publications on the topic of ILC considers linear-time-invariant or linear-parameter-varying systems, although many applications require nonlinear models to represent the system's dynamics sufficiently. An example for such an application is a robotic manipulator executing the same task repeatedly.

2 Approach

This paper adapts a general optimization-based ILC approach for arbitrary nonlinear systems [2] to be used for manipulators with n degrees-of-freedom in a closed-loop configuration. Having derived the nonlinear inverse dynamics $\mathbf{f}$, the closed loop can be written as

$$\mathbf{f}(\mathbf{y}_i(t), \mathbf{p}) = \mathbf{u}_i(t) = \mathbf{c}(\mathbf{r}_i(t), \mathbf{y}_i(t))$$

with iteration index i, the controller function $\mathbf{c}$, output $\mathbf{y} \in \mathbb{R}^{n\times 1}$, parameter vector $\mathbf{p}$, input $\mathbf{u} \in \mathbb{R}^{n\times 1}$ and reference $\mathbf{r} \in \mathbb{R}^{n\times 1}$. Existing ILC approaches for robot manipulators [3] use approximations of this nonlinear model, e.g. obtained by linearizing $\mathbf{f}$ along a desired trajectory $\mathbf{y}_\mathrm{d}$. In this research we consider the full nonlinear system dynamics and two possible modelling errors: unmodelled dynamics and model parameter mismatch. The developed learning approach consists of two steps that are executed at each iteration, as shown in Fig. 1. First, a model correction is computed by processing the torque and joint angular position measurements, $\mathbf{u}_{i,\mathrm{m}}(t)$ and $\mathbf{y}_{i,\mathrm{m}}(t)$, respectively. This correction can be parametric or nonparametric such that the above mentioned modelling errors can be compensated for, and is found by solving the optimization problem

$$\begin{aligned} \min_{\boldsymbol{\varepsilon}_{i+1}} \quad & \|\mathbf{u}_{i,\mathrm{m}} - \mathbf{f}(\mathbf{y}_{i,\mathrm{m}}, \mathbf{p}, \boldsymbol{\varepsilon}_{i+1})\| \\ \text{s.t.} \quad & \underline{\boldsymbol{\varepsilon}} \leq \boldsymbol{\varepsilon}_{i+1} \leq \overline{\boldsymbol{\varepsilon}} \end{aligned}$$

with the correction term $\boldsymbol{\varepsilon}$. The resulting correction is then used in the second step, the model inversion, to compute a reference update $\mathbf{\Delta r}_i$ by solving another optimization problem

$$\begin{aligned} \min_{\mathbf{\Delta r}_{i+1}} \quad & \|\mathbf{c}(\mathbf{y}_\mathrm{d} + \mathbf{\Delta r}_{i+1}, \mathbf{y}_\mathrm{d}) - \mathbf{f}(\mathbf{y}_\mathrm{d}, \mathbf{p}, \boldsymbol{\varepsilon}_i)\| \\ \text{s.t.} \quad & \underline{\mathbf{y}} \leq \mathbf{y}_\mathrm{d} + \mathbf{\Delta r}_{i+1} \leq \overline{\mathbf{y}} \end{aligned}$$

with $\mathbf{y}_\mathrm{d}$ being the iteration independent desired output and the resulting reference $\mathbf{r}_{i+1} = \mathbf{y}_\mathrm{d} + \mathbf{\Delta r}_{i+1}$, which is finally applied as the next iteration's input to the closed loop. This research focuses on the efficient solution of the optimization problems and the trade-off between convergence speed and robustness. The developed ILC approach is validated both in simulation and experimentally for a 6 degrees-of-freedom robotic manipulator.

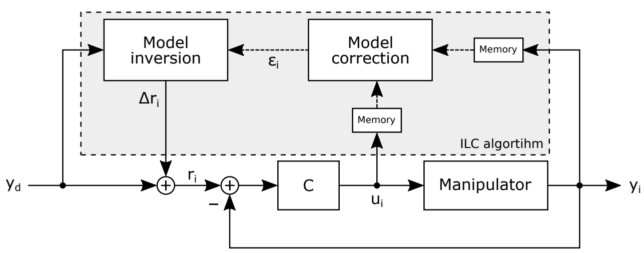

Figure 1: Closed-loop configuration and the ILC components

3 Acknowledgements

This work was supported by the Flanders' Make ICON project RoFaLC (Robust and Fast Learning Control). This work also benefits from KU Leuven-BOF PFV/10/002 Center of Excellence: Optimization in Engineering (OPTEC), and from the Belgian Network Dynamical Systems, Control and Optimization (DYSCO), initiated by the Belgian Science Policy Office.

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